The U.S. Labor Market during the Beginning of the Pandemic Recession*

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Abstract

Using weekly, anonymized administrative payroll data from the largest U.S. payroll processing company, we measure the deterioration of the U.S. labor market during the first two months of the global COVID-19 pandemic. We find that U.S. private-sector employment contracted by about 22 percent between mid-February and mid-April. Businesses suspending operations—perhaps temporarily—account for a significant share of employment losses, particularly among smaller businesses. Hours worked for continuing workers fell by 4.5 percent. We highlight large differences in employment declines by industry, business size, state of residence, and demographic group. Workers in the bottom quintile of the wage distribution experienced a 35 percent employment decline while those in the top quintile experienced only a 9 percent decline. Large differences across the wage distribution persist even after conditioning on worker age, business industry, business size, and worker location. As a result, average base wages increased by over 5 percent, though this increase arose entirely through a composition effect. Overall, we document that the speed and magnitude of labor market deterioration during the early parts of the pandemic were unprecedented in the postwar period, particularly for the bottom of the earnings distribution.

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1 Introduction

A novel coronavirus disease—later named COVID-19—originated in China in December 2019. The virus quickly spread to the rest of the world. The first confirmed case within the U.S. occurred in mid-January. On March 11th, the World Health Organization declared the COVID-19 outbreak a global pandemic. On the same day, the U.S. government banned travel from dozens of European countries. As of early May 2020, there were approximately 3.6 million confirmed COVID-19 cases worldwide resulting in roughly 250,000 deaths. Within the U.S., there were approximately 1.2 million confirmed COVID-19 cases resulting in 70,000 deaths as of early May.

In response to the global pandemic, almost all U.S. states have issued stay-at-home orders. On March 19th, California became the first state to set mandatory stay-at-home restrictions to slow the spread of the virus. In doing so, all non-essential services, including dine-in restaurants, bars, health clubs, and clothing stores, were ordered to close. Over the subsequent weeks, most other states put in place similar stay-at-home restrictions and non-essential business closures. Since mid-March, the U.S. federal government has urged Americans to restrict their domestic travel and to stay at home. Such policies have restricted labor demand by mandating the shuttering of many U.S. businesses. Additionally, the resulting income losses from layoffs and the desire for individuals to avoid exposure have reduced the demand for many goods and services; indeed, the labor market began weakening by early March, before the widespread imposition of stay-at-home orders.[1]

In this paper, we use administrative data from ADP–one of the world's largest providers of cloud-based human resources management solutions—to measure changes in the U.S. labor market during the early stages of this "pandemic recession."[2] Data from ADP have many advantages over existing data sources. First, ADP processes payroll for about 26 million U.S. workers each month. As discussed in both Cajner et al. (2018b) and Grigsby et al. (2019), the ADP data are representative of the U.S. workforce along many labor market dimensions. These sample sizes are orders of magnitudes larger than most household surveys, which measure individual labor market outcomes at monthly frequencies. Specifically, the ADP data cover roughly 20 percent of total U.S. private employment, similar to the BLS

[1] For example, the BLS jobs report for March, which estimated employment changes between mid-February and mid-March, already showed a private employment decline of about 700,000 and an increase in the unemployment rate of nearly a full percentage point.

[2] Recessions in the U.S. are designated by the National Bureau of Economic Research's Business Cycle Dating Committee. The Committee defines a recession as a "significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales." Although the current contraction has not officially been declared a recession, we are going to refer to it as such presumptively throughout the paper.

CES sample size. Second, the ADP data are available at weekly frequencies. Given that payroll processing is one of ADP's main service offerings, ADP has data on worker employment, hours, earnings, and wages for all client businesses for each pay period. After weekly payrolls are processed, ADP records these labor market variables for all workers in their client businesses. As a result, statistics on the health of the labor market can be observed in almost real time. Third, the ADP data contain both worker and business characteristics.[3] From our perspective as researchers, the data come anonymized such that no individual business or worker can be identified. However, each worker and business have a consistently defined, anonymized unique identifier so that workers and businesses can be followed over time. Collectively, the ADP data allow for a detailed analysis of high-frequency changes in labor market conditions in the first months of the likely current Pandemic Recession.

We find that paid U.S. private sector employment declined by about 22 percent between mid-February and mid-April 2020. This translates to a reduction in U.S. employment of about 29 million workers as measured in the payroll data. This downturn differs from modern U.S. recessions in both the speed and magnitude of its job loss. In no prior recession since the Great Depression has U.S. employment declined by a cumulative 7 percent. Across all prior recessions since the 1940s, peak employment declines occurred between 1 and 2.5 years after the recession started. The U.S. economy has already experienced a 22 percent decline in employment during the first two months of this recession.

We also show that labor market adjustments are occurring on both the extensive and intensive margin. Following individual workers over time, we find that hours worked for continuously employed workers fell by roughly 4.5 percent during March and April. Furthermore, the data allow us to distinguish *active* employment from *paid* employment. Active employment corresponds to the number of individuals active in the payroll system regardless of whether they were paid or not in a given pay period. Paid employment corresponds to the number of individuals issued a paycheck in a given pay period.[4] Differences between paid employment and active employment provide a measure of workers who were on temporary lay-off. Active employment only fell by about 14 percent during this time period. This suggests that a large fraction of workers who lost their job so far may be on layoffs that are intended to be temporary. Separately, we can also estimate the contribution of businesses suspending operations (perhaps temporarily) to the decline in aggregate employment. We

[3]For simplicity we refer to ADP payroll units as "businesses" throughout the paper, though in reality these units may be firms, establishments, or sub-firm groups of establishments. We discuss this further below.

[4]Active employees include wage earners with no hours in the pay period, workers on unpaid leave, and the like. Paid employees include any wage or salary workers issued regular paychecks during the pay period as well as bonus checks and payroll corrections.

find that roughly 16 percent of lost paid employment and almost 40 percent of lost active employment can be attributed to business exit, and exit is particularly prevalent among small businesses.

Importantly, the employment declines were disproportionately concentrated among lower-wage workers. Segmenting workers into wage quintiles, we find that 35 percent of all workers in the bottom quintile of the wage distribution lost their job—at least temporarily–during the first months of this recession. The comparable number for workers in the top quintile was only 9 percent. These broad patterns persist even after adjusting for worker and business characteristics. Employment declines were larger in service industries (such as leisure and hospitality industries) and in smaller businesses. These businesses disproportionately employ lower-wage workers. However, even conditioning on industry, business size, worker age, and worker location, we find that lower-wage workers are experiencing the brunt of employment declines during this pandemic-driven recession. Put another way, over 36 percent of the 29 million jobs lost during the first two months of this recession were concentrated among workers in the lowest wage quintile.

The massive decline in employment at the lower end of the wage distribution implies meaningful selection effects when interpreting aggregate data. For example, we document that average wages of employed workers have risen sharply—by over five percent relative to trend—during the last month in the United States. However, all of this increase is due to the changing composition of the workforce. As those with lower wages disproportionately leave employment, the composition of the remaining workforce tilts towards those with a higher wage. After controlling for worker fixed effects, there has been no substantive trend break in worker base wages during the beginning of the recession. However, as noted above, we do find some evidence that businesses are further reducing the compensation of workers by reducing their hours. To date, most of the labor market adjustment has been on the extensive margin of labor supply, with more modest adjustment on hours worked.

Our paper builds on the work of Cajner et al. (2018b), Cajner et al. (2020), and Grigsby et al. (2019). Cajner et al. (2018b) and Cajner et al. (2020) document that the payroll data from ADP can be used to measure high-frequency changes in employment within the United States. Specifically, they show that changes in measured employment within the ADP data track well with U.S. employment changes reported in official statistics. They also highlight that the ADP data are reasonably representative of U.S. businesses, with a wide range of coverage across business size, industry, and geography. Likewise, Grigsby et al. (2019) use the ADP data to document nominal wage rigidities within the U.S. economy. They also provide evidence that the ADP wage and earnings distribution matches well aggregate statistics from other sources. In this paper, we use what we learned from our collective past work to measure changes in labor market conditions at the beginning of the current downturn.

There is a growing literature studying the effects of the COVID-19 virus on the macroeconomy. Many of these papers model and quantify the trade-off between minimizing adverse health events and minimizing economic disruptions. Papers in this vein include Alvarez et al. (2020), Eichenbaum et al. (2020), Jones et al. (2020), Kaplan et al. (2020) and Berger et al. (2020). Guerrieri et al. (2020) develop a model showing how supply shocks can cause large reductions in aggregate demand. Ludvigson et al. (2020) use historical data to forecast the macroeconomic impact of COVID-19. Our work complements these papers by providing a set of moments regarding labor market changes—both overall and disaggregated by sector, location and worker characteristics—to help discipline these models. In that sense our paper is related to Baker et al. (2020c) who use proprietary financial data to measure the changes in consumption and debt during the first few weeks of the recent economic slowdown.

There are other papers providing real-time data about the current macroeconomic environment. Bartik et al. (2020b) surveyed roughly 6,000 small businesses and documented that these small businesses dramatically reduced their employee counts since January; and Bartik et al. (2020a) use high-frequency data from Homebase to track small business employee hours, finding steep drops in hours through March with some stabilization late in the month. Kurmann et al. (2020) benchmark Homebase data for the leisure and hospitality sector to official sources, similar to our approach, and thereby argue that the sector has seen a total employment decline of almost 12 million jobs during the COVID-19 episode. Baker et al. (2020a) document the enormous increase in economic uncertainty surrounding the current pandemic, while Baker et al. (2020b) show the unprecedented nature of recent stock market movements. Lewis et al. (2020) use a combination of high-frequency economic data from various sources—including retail sales, consumer sentiment, unemployment claims, and electricity consumption—to create a weekly measure of economic activity. Brynjolfsson et al. (2020) and Coibion et al. (2020) use household survey data from Google Consumer Surveys and the Nielsen Homescan panel, respectively, to measure the decline in employment during March and April 2020. Two recent papers—Dingel and Neiman (2020) and Mongey et al. (2020)—predict heterogeneous employment losses during the current recession based on job characteristics, such as the ability to work at home or whether the sector requires social interaction. Our paper complements these other papers by using real-time payroll data for a reasonably representative one-sixth of the labor force to measure a variety of actual real time labor market outcomes.

The paper is organized as follows. We begin in Section 2 by describing the ADP data and our methodology for measuring changes in labor market activity. In Section 3, we highlight the decline in employment for the aggregate economy during the first two months of this recession and compare these declines to prior recessions. We also document changes in aggregate hours worked and rising business exit rates. Section 4 highlights the heterogeneous changes in employment by industry, business size, worker age, worker gender, and location. Section 5 documents the distributional effects of the employment declines across workers in various wage quintiles. Section 6 discusses changes in wages during the beginning of this recession. Section 7 concludes.

2 Data and Methodology

We use anonymized administrative data provided by ADP. ADP is a large international provider of human resources services including payroll processing, benefits management, tax services, and compliance. ADP has more than 810,000 clients worldwide and now processes payroll for over 26 million individual workers in the United States per month. The data allow us to produce a variety of metrics to measure high-frequency labor market changes for a large segment of the U.S. workforce.

2.1 Measuring Employment Changes

We use two separate data sets to measure high-frequency labor market changes. In this section we introduce a business-level data set, the subsequent section covers a worker-level data set.[5] The business-level data set reports payroll information during each pay period. Each business' record is updated at the end of every pay period. The record consists of the date payroll was processed, employment information for the pay period, and many time-invariant business characteristics such as NAICS industry code.[6] Business records include both the number of individuals employed ("active" employees) and the number of paychecks issued in a given pay period ("paid" employees). Active employees include wage earners with no hours in the pay period, workers on unpaid leave, workers who are temporarily laid-off and the like. Paid employees include any wage or salary workers issued regular paychecks during the pay period as well as those issued bonus checks or any other payments.

The data begin in July 1999 but are available at a weekly frequency only since July 2009. As shown in Cajner et al. (2018a), ADP payroll data appear to be quite representative of

[5]When accessing the microdata, we follow a number of procedures to ensure confidentiality. Business names are not present in the data.

[6]Note that we use the term "business" throughout the paper to denote ADP clients. Often, entire businesses contract with ADP. However, sometimes establishments or units within a firm contract separately. The notion of business in our data is therefore a mix of Census Bureau notions of an establishment (i.e., a single operating business location) and a business (i.e., a collection of establishments under unified operational control or ownership).

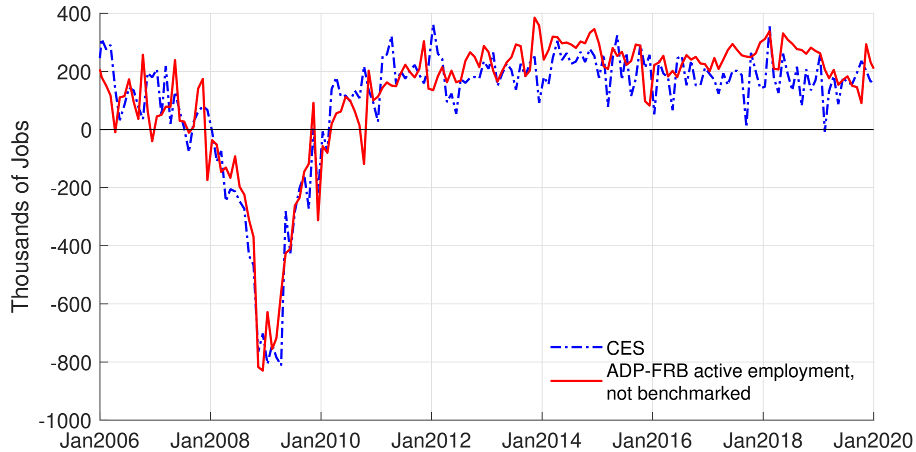
the U.S. economy, though the data somewhat overrepresent the manufacturing sector and large businesses (as compared to the QCEW universe of establishments). We address these issues by reweighting the data as explained below. The process of transforming the raw data into usable aggregate series is complex, and we refer the interested reader to Cajner et al. (2018a) for details of the creation of the ADP-Federal Reserve Board (ADP-FRB) high frequency employment series, which we use in some tables and figures in this paper. In short, we calculate the weighted average growth of employment at businesses appearing in the data for two consecutive weeks. The restriction to "continuers" for this index allows us to abstract from changes in the size of ADP's client base over time. However, below, we will explicitly discuss business exit during the early part of the 2020 "recession." For businesses that do not process payroll every week (for example, businesses whose workers are paid biweekly), we create weekly data by assuming the payroll in the missing intermediate period is what is observed in the next period the business processes payroll. We build a weekly time series of employment for each business, estimating employment at the business each Saturday.[7]

Measured client growth rates are weighted by business employment and further weighted for representativeness by size and industry; for comparability with BLS data, here we treat ADP payroll units as establishments for weighting purposes. We use March QCEW employment counts by establishment size and two-digit NAICS as the target population, and we update the weights yearly.[8] Cumulating the weekly growth rates yields a weekly index level for employment. We benchmark the data annually to QCEW employment levels and use a forward benchmarking projection akin to the CES birth and death model. While we believe benchmarking is important since the QCEW (when available) represents the most complete and accurate estimate of employment, the raw ADP data align well with official sources even before benchmarking. Figure 1 compares the *monthly* change in employment in the unbenchmarked ADP-FRB series to the (QCEW-benchmarked) CES series through February 2020. The series track each other very closely, indicating that both are picking up the same underlying signal (i.e., true U.S. payroll growth).

[7]Technically, the employment concept is business employment for the pay period that includes the Saturday in question, as we cannot observe change within pay period. Lacking any information on events within a pay period, we assume that businesses adjust their employment discretely at the beginning of each pay period and that employment is constant within the pay period. This assumption is consistent with the typical practice of human resource departments, according to which job start dates often coincide with the beginning of pay periods. It is also analogous to the CES methodology, which asks for employment for the pay period including the 12th of the month.

[8]Formally, let $w_{j,t}$ be the ratio of QCEW employment in a size-industry cell j to employment from ADP data in cell j in week t, let $C(j)$ be the set of ADP businesses in cell j, let $e_{i,t}$ be the employment of the i'th business, and let $g_{i,t} = \frac{e_{i,t}-e_{i,t-1}}{e_{i,t-1}}$ be the weekly growth rate of business i. Aggregate growth is estimated as $g_t = \frac{\sum_{j=1}^{J} w_{j,t-1} \sum_{i\in C(j)} e_{i,t-1} g_{i,t}}{\sum_{j=1}^{J} w_{j,t-1} \sum_{i\in C(j)} e_{i,t-1}}$.

Figure 1: Historical Monthly Change in Private Payroll Employment: ADP-FRB Series vs. CES



Notes: Source CES, ADP, authors' calculations.

Returning to the weekly data, the last step is to seasonally adjust the series using the methods of Cleveland and Scott (2007), which combine a fixed coefficient regression with locally weighted regressions on trigonometric functions. Note that the Cleveland and Scott approach was employed to seasonally adjust the weekly unemployment claims data.[9] Given the magnitudes of the changes in the labor market observed during March and April of 2020, we use non-concurrent seasonal factors (i.e., factors estimated prior to the onset of the downturn.)

Since the primary focus of this paper is on weekly data, it is worth noting the distribution of pay frequencies in the ADP data. As of March 2017, 22 percent of ADP clients were issuing paychecks weekly, 46 percent biweekly, 21 percent semi-monthly, and 11 percent monthly (in terms of employment, these shares are 23 percent, 55 percent, 18 percent, and 4 percent, respectively). These fractions are not far from what the BLS reports.[10]

Finally, it is worth noting that we only measure employment declines once we observe a business's regularly scheduled payroll. This can mean that there is some lag in our measurement. For example, suppose a business pays all of its workers biweekly. We will observe the business's payroll in week t and then again in week $t+2$. Suppose the business lets 20 percent of its workers go in week $t+1$. We would not be able to infer this paid employment decline until week $t+4$, since those workers worked some in the $t+2$ pay period. However, if

[9]For the weekly seasonal adjustment, we specifically control for holiday weeks, including Thanksgiving, Memorial Day, Labor Day, New Years, Christmas, and July 4th. We also account for strong employment weeks leading up to holidays and the seasonal employment related to Christmas. Special thanks to Charlie Gilbert for his assistance with seasonal adjustment.

[10]See BLS (2019) "Length of pay periods in the Current Employment Statistics survey."

the workers were permanently let go (as opposed to being temporarily laid-off), we would be able to observe active employment declines in week $t + 2$. All of this is to say that our measurement may, at times, be shifted a week or two relative to when a hire or separation took place. This is part of our motivation for focusing on the pay period employment concept, discussed above.

2.2 Measuring Hours, Wages, and Worker Demographics

The business-level data reports payroll aggregates for each business. For a very large subset of businesses, we also have access to their anonymized de-identified individual-level employee data.[11] That is, we can see detailed anonymized payroll data for individual workers. As with the business data, all identifying characteristics (names, addresses, etc.) are omitted from our research files. Workers are provided an anonymized unique identifier by ADP so that workers may be followed over time. We observe various additional demographic characteristics such as the worker's age, gender, tenure at the business and residential state location. We also can match the workers to their employer. As with the business-level data described above, we can observe the industry and business size of their employers.

The benefits of the employee data relative to the business data described above are two-fold. First, we can explore employment trends by worker characteristics such as age, gender, and initial wage levels. This allows us to discuss the distributional effects of the current recession across different types of workers. Second, the individual-level data allow us to measure additional labor market outcomes such as hours worked and wages. We also know the frequency at which the worker is scheduled to be paid and whether the worker is paid hourly or is salaried. The drawbacks are also twofold: First, the employee data contains a subset of ADP's clients, while the business-level data represents all of ADP's client base. Second, the business level data allows us to observe active employment, that is, employment counts including those workers that are in the payroll system but not receiving paychecks in a given pay period.

The individual-level data allows us to observe the worker's contractually obligated pay rate as well as their gross earnings during the pay period. For hourly workers, the per-period contract pay rate is simply the worker's base hourly wage. For salaried workers, the per-period contract rate constitutes the pay that the worker is contractually obligated to receive each pay period (e.g., weekly, biweekly, or monthly). For workers who are paid hourly, we

[11]The data for our employee sample skew towards employees working in businesses with at least 50 employees. This is the same data used in Grigsby et al. (2019). While the data come from employees mostly in businesses with more than 50 employees, there is representation in this data for employees throughout the business size distribution. Again, we weight these data so that it matches aggregate employment patterns by industry and business size.

also have administrative records of how many hours they worked during the pay period. For workers who are salaried, the hours are almost always set to 40 hours per week for full-time workers and some fraction of 40 hours per week for part-time workers. For example, workers who are half-time are usually set to 20 hours per week. As a result, the hours for salaried workers are more indicative of full-time status than actual hours worked.

When reporting hours, employment, and wage statistics using the employee-level sample, we also weight the data to ensure that it is representative of the U.S. population by 2-digit industry and business size. To create the weights for this part of our analysis, we use data from the U.S. Census' 2017 release of the Statistics of US Businesses. Specifically, we weight the ADP data so that it matches the share of businesses by 2-digit NAICS industry and business size. As highlighted in Grigsby et al. (2019) the weighted employee-level data is representative of the U.S. labor market on many dimensions.

To construct employment indices, we exploit the high-frequency nature of the ADP data. To facilitate our measurement using the employee data, we limit our attention to workers paid weekly or biweekly for these analyses to avoid time aggregation issues. These account for about 80 percent of all employees in our employee sample. Unsurprisingly, this is nearly identical to the share of weekly and biweekly employees in the business-level sample described above.[12] Biweekly workers are generally paid either on every even week (e.g. the 4th, 6th, and 8th week of the year) or on every odd week. We designate biweekly workers to be "even biweekly" workers if their regularly scheduled paychecks are disbursed on even weeks, or "odd biweekly" workers if their regularly scheduled paychecks are disbursed on odd weeks. We then sum all paychecks—earnings and hours—in a two-week period to the nearest subsequent even week for even biweekly workers, and the nearest subsequent odd week for odd biweekly workers. We additionally sum all paychecks in a given week for all weekly workers. The result of this is an individual-by-week panel. We then produce separate indices for weekly, biweekly-even, and biweekly-odd employees and then combine the indices into an aggregate employment index. We use these indices when computing employment changes by worker characteristics (age, sex, worker location, and wage percentile). We compute hours and wage indices similarly. However, the panel nature of our data allows us to make indices for hours worked and wages following a given worker over time. This allows us to control for the changing selection of the workforce at the aggregate level over this period.

In all the work that follows, we will indicate whether we are using (1) the business-level data—which includes all businesses but not any worker characteristics—or (2) the employee-level data—which includes workers from most (but not all) businesses but does

[12]Our preliminary evidence suggests that workers paid semi-monthly look nearly identical to those paid bi-weekly.

include worker characteristics. For all aggregate results, the weighted employment changes found within both data sets are nearly identical during the beginning of the Pandemic "Recession." Lastly, we have access to the employee-level data through the pay week ending April 25th. Given most people are paid biweekly, this allows us to measure employment declines through April 11th. Workers who do not show up in the April 25th payroll data were therefore displaced sometime prior to April 11th.

3 Aggregate Labor Market Changes during the Pandemic "Recession"

This section highlights the labor market changes in the United States during the first six weeks of the "recession." We focus first on employment declines, then business exit, then changes in hours worked for continuing workers. We end this section by comparing the decline in employment so far during the "recession" to the decline in employment during the beginning of other historical U.S. recessions.

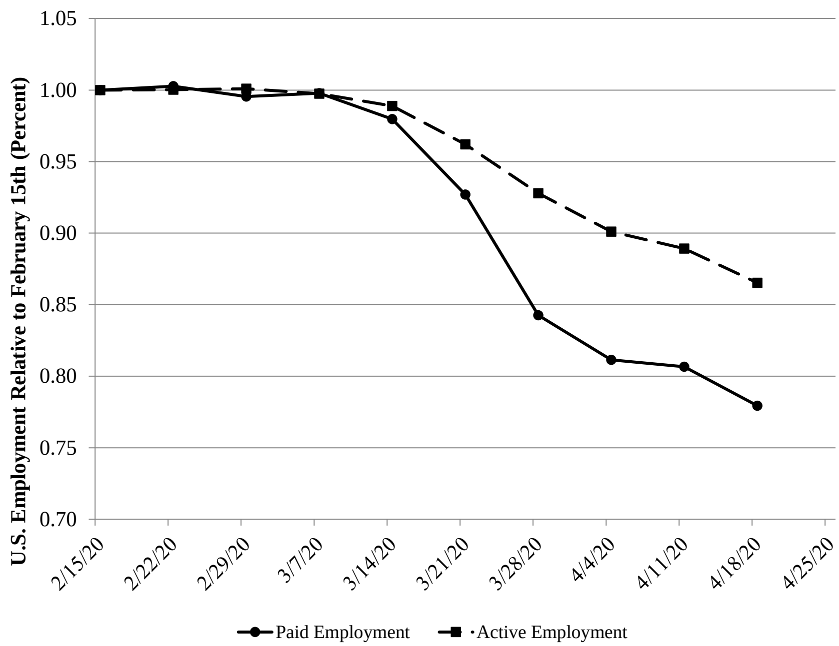
3.1 Declining Employment

Figure 2 shows our estimated aggregate employment changes spanning the payroll week covering Feb 15th through the payroll week covering April 18th using the ADP business-level data. Importantly, this figure is inclusive of both employment changes at continuing businesses and employment losses among businesses that drop out of the sample (which may be suspending operations temporarily or indefinitely, and we sometimes refer to as exiting businesses). The changes are plotted as percent changes relative to February 15th. The figure shows trends in paid employees (solid line) and active employees (dashed line). Between mid-February and mid-April, paid employment in the U.S. has fallen by roughly 22 percent, and active employment has fallen by about 14 percent. The sharper drop in paid employment is to be expected if, as of now, many businesses are placing their workers on temporary layoff.

Given that U.S. private employment in February of 2020 was 129.7 million workers, the ADP data suggest that total employment in the U.S. fell by about 29 million. This is larger than the 26 million new unemployment claims reported as of April 18th which covers the same time period as our ADP data. The unemployment claims are likely a lower bound on actual job loss, given that some workers may be slow to file for UI claims while others may be ineligible.[13] There is also a literature highlighting that not all eligible applicants file

[13] The sheer number of unemployed has led to long lines and generated strain on the UI system. See,

Figure 2: Aggregate Active and Paid Employment



Notes: Figure shows the trend in employment within the ADP business-level sample through the April 18th pay periods. Employment changes are relative to February 15th. The solid black line (circles) shows the trend in payroll employment. The dashed black line (squares) shows the trend in active employment. All trends are weighted such that the ADP sample is representative by business size crossed with 2-digit NAICS industry.

for unemployment claims.[14] Conversely, we are weighting to match private employment and therefore will not capture employment changes in the public sector.[15] Overall, the decline in employment that occurred during the first month of the recession was massive.[16]

3.2 Business Exit

The results above include the contributions of both businesses that suspend operations (whether temporarily or permanently) and businesses that continue operating. Separating these groups is useful, particularly given the concerns that an economic recovery may be sluggish if many businesses exit permanently rather than just shrinking or shutting down temporarily. Figure 3 shows the dynamics of employment at *continuing* businesses (in red) alongside the aggregate series from Figure 2. Continuing businesses are defined as those that have continued to pay at least some workers between February 15th and a given reference date. Continuing businesses experienced significant declines in employment over the course of March and April, roughly mirroring the aggregate trends. However, the declines are not as large as the aggregates, as a substantial amount of exit took place.[17] In particular, an alarming 40 percent of lost active employment and 16 percent of lost paid employment (up through April 18th) were due to business exit.[18]

This apparent wave of business exits could have long-lasting implications. To the extent that business exits are permanent (an important topic for future research), these jobs should not be expected to return quickly. Workers associated with these jobs will have to be matched to new positions at existing businesses – whose health during the recovery period is still highly uncertain – or new businesses. Business exit also means permanently lost intangible capital and, to some extent, even the destruction of physical capital given costly capital reallocation. Moreover, a wave of business exits could permanently change the physical economic landscape of communities, where specific businesses – including small businesses –

for example, https://abcnews.go.com/Business/struggle-apply-unemployment-continues-country/story?id=70042620, accessed April 11, 2020.

[14] For a recent example, see Chodorow-Reich and Karabarbounis (2016).

[15] The ADP data also covers public sector employment. We highlight changes in the public sector in Section 4 below. Given aggregate employment in the public sector and the declines we are finding within the ADP data for this sector, this would add an additional 400,000 jobs lost through mid-April.

[16] Note that the data in Figure 2 are not seasonally adjusted. Appendix Figure A1 shows that the results for paid employment declines are quantitatively similar when the data are purged of outliers, adjusted for predictable revisions, and seasonally adjusted using the methods of Cleveland and Scott (2007)

[17] Here "exit" means not processing payroll with ADP in recent weeks. Estimates based on this concept can revise, as some businesses inevitably process payroll later than would be expected. These revisions are also why the series for continuing businesses extend to April 25th while the series inclusive of entry and exit end on April 18th; The more recent data on exit are too noisy to be informative.

[18] These calculations are based on the contributions to growth. They do not include the effects of entry, which are small over such a short horizon.

form a critical component of local economic life.

Business exit also interferes with the *measurement* of the labor market. The Current Employment Statistics (CES) survey produced by the U.S. Bureau of Labor Statistics relies only on reports from continuing businesses when estimating the monthly change in employment, filling in the net contribution of business birth and death with an imputation procedure and a backwards-looking ARIMA model. As a result, unforecasted changes in the contributions of birth and death result in errors in the high-frequency CES estimates. These errors are typically small, but they were large in the Great Recession and are likely to be large in the near term of this recession, as the pandemic's effect on birth and death is certainly not accounted for in the net birth-death forecast.[19] The CES benchmark revision article for 2009 reported that the primary driver of revisions to CES for the March 2008 to March 2009 period was forecast error in the birth/death model (Bureau of Labor Statistics (2009)), which had difficulty capturing the dramatic change in business entry and exit patterns of that recessionary episode.[20] In the current episode, the monthly CES print for March relied on model estimates derived from data for mid-2019, long predating the rapid onset of the COVID-19 pandemic; the BLS will modify birth-death treatment in coming releases (beginning with the April release), but it may still be difficult to accurately measure birth and death given sampling limitations. Our analysis provides real-time estimates of employment losses due to business exit.

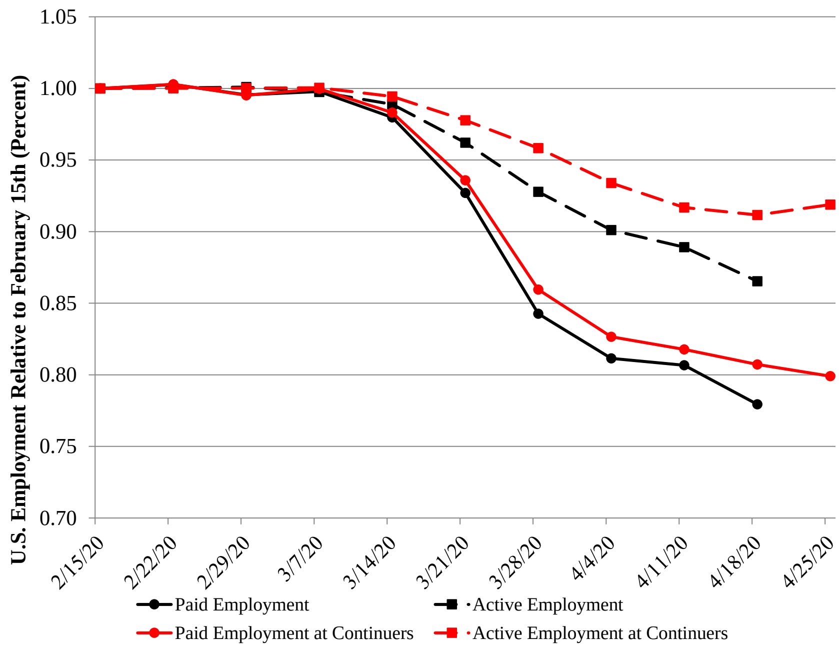
3.3 Declining Hours

Figure 4 shows the decline in aggregate employment, aggregate hours and the hours of continuing hourly workers during the beginning of the recession using the ADP employee sample. The ADP employee-level data measure employment through April 11th. The darker bars show changes from February 15th through March 7th while the lighter bars show changes from February 15th through April 4th. We include the change from February 15th through

[19]The BLS has announced that the April 2020 CES release (scheduled for May 8, after the completion of the present draft of this paper) will feature a modified approach to birth-death modeling to improve estimates under the current unusual circumstances; we do not know what modifications the BLS plans to implement. Generally, establishment births and deaths are difficult or impossible to measure using the rigorous sampling techniques employed by the BLS for CES monthly employment estimates. The BLS typically uses two procedures to estimate birth and death contributions in a rigorous manner: an imputation algorithm that treats all non-responders as deaths and imputes their employment to births (based on the strong historical relationship between births and deaths), and the net birth-death ARIMA model (see Mueller (2006)). Both of these procedures, while scientifically based and quite accurate under most conditions, are likely to create large errors under current circumstances.

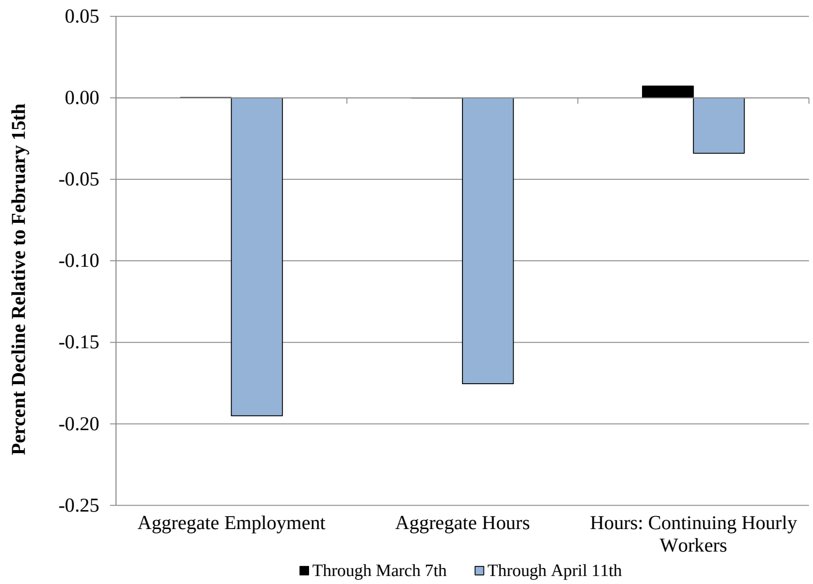
[20]Subsequently, the BLS increased the frequency at which it re-estimates the model (Bureau of Labor Statistics (2020)); however, under the revised standard procedure in effect through at least March 2020, birth-death estimates continue to rely on forecasts that jump off data from 10 to 12 months earlier.

Figure 3: Aggregate & Continuing Employment Declines



Notes: Figure shows the trend in employment within the ADP business-level sample through the April 18th/April 25th pay periods. Employment changes are relative to February 15th. The solid black line (circles) shows the trend in aggregate payroll employment. The dashed black line (squares) shows the trend in aggregate active employment. The solid red line shows the trend in payroll employment at businesses which were operating both on the reference date and February 15th, the dashed red line shows active employment for the same group. Aggregate series end one week earlier than the continuer series because late-arriving payrolls render the most recent weeks too noisy to be informative. All trends are weighted such that the ADP sample is representative by business size crossed with 2-digit NAICS industry.

Figure 4: Employment and Hours using Employee Data



Notes: Figure shows the change in employment and hours within the ADP employee-level sample through March 7th (dark bars) and April 11th (lighter bars). Employment changes are relative to the week of February 15th. The first and second series measures the change in aggregate employment and hours, respectively. The third series measures the change in hours worked for hourly workers who remain continuously employed during the period. All data are weighted such that the sample is representative by business size crossed with 2-digit NAICS industry.

March 7th to show that there were no pre-trends in the series. By April 11th, employment fell by roughly 20 percent, which is nearly identical to the employment declines through April 11th numbers found in the business-level sample highlighted in Figure 2. The fact that the two data sources yield similar results is comforting given that we will be toggling between the two series depending on our analysis.

The second column shows the change in aggregate hours. For this figure we use the reported hours of both hourly workers and salaried workers, noting that the reported hours of salaried workers are almost always set to 40 hours per week. We include the salaried workers to see if any of them experienced formally reduced hours by their businesses as result of them being furloughed. We note that hours worked by salaried workers is likely better measured in household surveys. With that caveat in mind, we find that the decline in aggregate hours is similar to the decline in aggregate employment during this time period: 17.5% vs. 19.5%. The third column measures reported hours worked for hourly workers who remain continuously employed during the sample period. In particular, we follow a given worker over time and measure the growth rate in their hours conditional on them remaining employed throughout the sample period. We do this only for hourly workers who have meaningful notions of hours worked: these are the hours on which the worker's compensation is based. Continuing hourly workers, as a whole, have reduced their hours by about 4.5 percent over the first month of the recession. Some of the decline in aggregate labor inputs is occurring on the intensive margin of employment.[21]

3.4 Historical Perspective

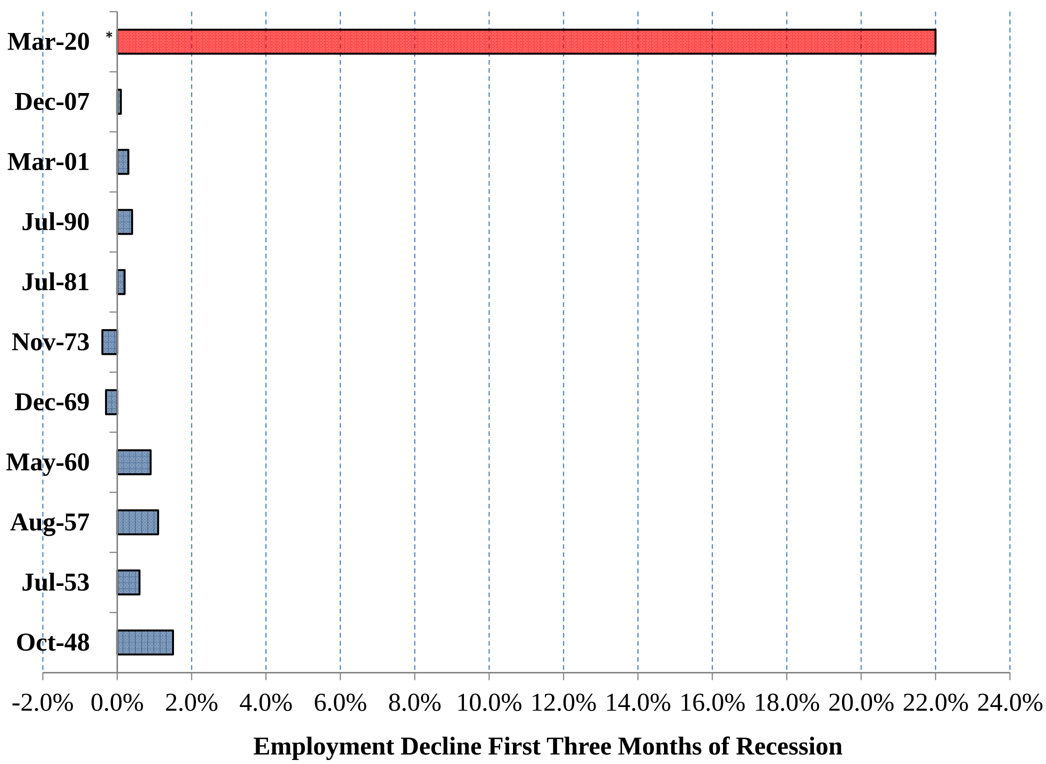
To put these results in context, consider the employment changes in all past U.S. recessions since 1940. We use NBER recession dates to define the start and end of each recession. We use total non-farm employees from the U.S. Bureau of Labor Statistics as our measure of total employment for the historical recessions. Figure 5 shows the actual employment decline during the first three months of the prior ten U.S. recessions. In all prior recessions, employment declines occurred slowly. No prior recession had an employment decline greater than 1.3 percent during the first three months after the recession started. The Great Recession started among the slowest - during the first three months of the Great Recession, employment only fell by 0.1 percent. In contrast, the first month of the current downturn has seen employment fall by 22 percent. The speed at which the labor market has declined during the current "recession" is unprecedented in modern U.S. economic history.

Table 1 displays various additional labor market statistics about the prior ten U.S. recessions. The first column of the table reports the start date of the recession while the second column reports how long the recession lasted. The third column reports the maximum decline in employment that occurred during the recession. The fourth column reports the time it took from the start of the recession to reach the maximum employment decline. The last column reports the peak unemployment rate during the recession which almost always occurred within a month or two of the peak employment decline.

Table 1 provides a few primary takeaways. First, the maximum employment decline in all of the previous ten recessions was less than 7 percent. The recession with the largest employment decline—the Great Recession—saw employment drop 6.5 percent. Not only is the current recession notable for the speed of its change, it is also historic in its magnitude; even focusing on active employment among continuing businesses, thereby omitting likely temporary layoffs and uncertain estimates of business exit, we see a cumulative decline of

[21] As seen from the figure, the decline in aggregate hours is smaller than the decline in aggregate employment despite declining hours worked for continuing workers. As we highlight below, this is because there is a negative co-variance between initial hours worked and the propensity for job loss: workers with low initial hours were more likely to lose their job during the recession.

Figure 5: Employment Decline During First Three Months of Historical Recessions



Notes: Figure shows the percentage decline in aggregate employment during the first three months of historical recessions. Data for historical recessions come from the monthly employment numbers from the U.S. Bureau of Labor Statistics. Recession start dates (month-year) defined by the National Bureau of Economic Research. (*) The March 2020 recession has not been officially defined as a recession; we are doing so presumptively. Employment decline for March 2020 comes from ADP payroll data and only measures employment declines during the first two months of the recession.

Table 1: Employment Declines During Prior U.S. Recessions

Recession Start Month	Length of Recession	Maximum Employment Decline	Time To Maximum Decline	Peak Unemployment
Nov 1948	11 mos.	-5.2%	12 mos.	7.9%
July 1953	10 mos.	-3.4%	13 mos.	6.1%
Aug 1957	8 mos.	-4.3%	10 mos.	7.5%
April 1960	10 mos.	-2.3%	11 mos.	7.0%
Dec 1969	11 mos.	-1.2%	12 mos.	6.1%
Nov 1973	16 mos.	-1.9%	18 mos.	9.0%
July 1981	16 mos.	-3.1%	17 mos.	10.8%
July 1990	8 mos.	-1.4%	11 mos.	7.8%
Mar 2001	8 mos.	-2.0%	26 mos.	6.2%
Dec 2007	18 mos.	-6.5%	27 mos.	10.0%

Notes: Table shows labor market statistics for the last ten recessions in the United States using data from the Bureau of Labor Statistics. The first column denotes the month the recession started. The second column reports how long the recession lasted. Columns 3 reports the peak employment decline during the recession. Column 4 denotes how many months it took after the start of the recession to reach the peak employment decline. The last column report the maximum unemployment rate after the start of the recession.

13 percent by April 18th. Second, the peak employment decline occurred 27 months into the Great Recession. In all recessions, the peak employment declines occurred at least one year into the recession. In some recent recessions—where job-less recoveries were prevalent—the peak employment rate declines occurred between 1.5 and 2.5 years after the recession started—and months after the recession ended.

As seen from column 5 of Table 1, peak unemployment rates during past recessions ranged from 6 to 11 percent. The 1973, 1981, and 2007 recessions all saw aggregate unemployment rates rise above 9 percent. Monthly employment data for the U.S. economy were not consistently collected during the Great Depression. As reported in Margo (1993), scholars have estimated that the unemployment rate was 8.7% in the first year of the Great Depression (1930), 15.9% in the second year, 23.6% is the third year, and 24.9% in the fourth year. A decline in employment of around 22% would likely result in an increased aggregate unemployment rate during the current recession that would be roughly in the range of unemployment rates observed in the second year of the Great Depression, absent large swings in the labor force participation rate.[22] In summary, the current U.S. recession is unprecedented

[22] Coibion et al. (2020) find from early surveys that the labor force participation rate fell sharply in early April 2020, suggesting that unemployment rates may not decline as much as employment-to-population ratios.

Table 2: Paid and Active Employment Changes by Supersector

Industry	Active Employment Change	Paid Employment Change
Leisure and Hospitality	-19.8%	-45.1%
Trade, Transportation, and Utilities	-9.0%	-17.7%
Other Services	-5.7%	-17.3%
Construction	-4.9%	-14.5%
Education and Health Services	-0.8%	-13.4%
Manufacturing	-5.9%	-11.8%
Professional and Business Services	-6.0%	-11.5%
Information Services	-4.8%	-13.4%
Mining	-7.2%	-7.1%
Financial Services	-3.0%	-5.8%

Notes: Table shows decline in active (column 1) and paid (column 2) employment (column 1) using our business sample for supersectors. Employment declines are measures between the weeks of February 15th and April 25th, 2020 and are weighted such that aggregate employment in the business level sample matches employment shares by business size within each 2-digit industry bin.

in modern U.S. history both in the magnitude and speed of its employment decline.

4 Heterogeneity by Industry, Business Size, Location and Demographics

In this section, we examine the changing labor market outcomes across business and worker characteristics. We highlight patterns separately by industry, business size, worker age, worker gender, and worker state of residence.

4.1 Industry

The declines in employment documented in Figure 2 are broad-based throughout the economy but also exhibit substantial heterogeneity across industries. Table 2 shows patterns by supersector, while Table 3 shows patterns for two-digit NAICS industries. The declines are measured from February 15th through late-April.

Table 2 uses data from our business-level sample and shows declines in active and paid employment for each supersector, relying on the ADP-FRB index concept in which exiting businesses do not influence the numbers during the pay period in which they exit. Unsurprisingly, the largest declines are seen in the Leisure and Hospitality sector, where active employment fell almost 20% and paid employment fell about 45%. All sectors saw substantial declines in paid employment, though active employment in the education and health sector was little changed. Overall, declines in paid employment were much larger than declines in active employment, consistent with our aggregate results, though these discrepancies vary some by sector. In most sectors, the active employment decline is between 40 and 50 percent of the paid employment decline. A notable exception to the upside is the Mining sector, where almost all the decline in paid employment reflects declining active employment; Mining includes oil exploration, production, and support industries, where oil prices recently plummeted due initially to supply developments rather than COVID-19 (though COVID-related demand weakness has followed). Our data suggests that much of the resulting employment decline in Mining reflects permanent layoffs. Conversely, the Education and Health Services sector has seen little change in active employment despite a 13 percent drop in paid employment. We provide figures showing weekly cumulative changes by sector in the appendix.

Table 3 shows there is a large amount of heterogeneity with respect to employment declines even within supersectors. For this table we focus on our employee sample which allows us to also measure the observed decline in hours worked for continuously employed workers within the industry.[23] The largest declines in employment were in sectors that require substantive interpersonal interactions.[24] In the first month after the start of the Pandemic Recession, paid employment in the "Accommodation and Food Services" and "Arts, Entertainment and Recreation" sectors (i.e., leisure and hospitality) both fell by over 50 percent. Two-digit industries that experienced declines in employment of about 20 percent through mid-April include "Other Services" (which includes many "local" or neighborhood businesses like laundromats and hair stylists), "Real Estate/Rental/Leasing", and "Administrative and Support". Despite a boom in emergency care treatment within hospitals, the "Health Care and Social Assistance" industry has experienced a 13 percent decline in employment.[25] "Retail Trade" declined by 13 percent since early March. That decline masks even more heterogeneity within this sector. Some sub-industries like Clothing

[23]The slight differences between the results in Table 2 with the business sample and Table 3 with the employee sample for overlapping sectors is due to both differential weighting procedures and differential coverage of businesses in the employee sample relative to the full business sample.

[24]Mongey et al. (2020) conjecture that workers who must interact frequently with others will have the largest employment declines during the pandemic recession.

[25]Despite the increase in emergency care within hospitals, hospitals overall are seeing employment declines. Non-emergency hospital services have declined substantially, reducing hospital revenues and causing hospitals to shed workers. See, for example, "During a Pandemic, an Unanticipated Problem: Out of Work Health Workers" April 3rd, 2000 *New York Times*.

Table 3: Paid Employment and Hours Changes By 2-Digit Industry

Industry	Paid Employment Change: All	Hours Change: Continuing Hourly Workers
Arts, Entertainment and Recreation	-56.4%	-19.2%
Accommodation and Food Services	-52.9%	-18.6%
Other Services	-23.6%	-8.6%
Administrative and Support	-19.8%	-5.1%
Real Estate, Rental and Leasing	-19.8%	-5.8%
Transportation and Warehousing	-17.8%	-2.8%
Manufacturing	-17.5%	-8.0%
Information Services	-16.1%	-2.1%
Educational Services	-15.9%	-4.0%
Retail Trade	-13.3%	-10.0%
Construction	-12.9%	-4.3%
Health Care and Social Assistance	-12.9%	-3.4%
Wholesale Trade	-10.9%	-9.4%
Professional, Scientific, and Tech Services	-8.9%	-4.3%
Public Administration	-8.2%	-2.5%
Finance and Insurance	-3.3%	-0.9%
Agriculture	0.5%	-1.2%
Utilities	3.8%	-0.5%

Notes: Table shows decline in paid employment (column 1) and hours worked for continuing workers who are paid hourly (column 2) for two-digit NAICS industries between the pay weeks of February 15th and April 11th, 2020. Both columns use data from the employee level sample. For this table, we report unweighted changes.

Stores saw declines in paid employment of 40 percent, while Health and Personal Care stores have only seen a 7 percent decline in paid employment. Finally, both the Agriculture industry and the Utilities industry saw slight employment increases during the early part of this recession. Industries that employ higher-educated workers—like Finance/Insurance and Professional/Scientific Services—only saw very small employment declines thus far.

There has been a lot of discussion about the ability of a worker to be able to work from home as a form of insurance against job loss during the current pandemic driven recession. For example, Dingel and Neiman (2020) and Mongey et al. (2020) both create measures of a worker's ability to work at home using detailed occupation-level task data. Dingel and Neiman (2020) provide measures of workers' ability to work at home at the level of 3-digit

NAICS industry.[26] Their measure ranges from zero to 1 with a larger number implying that more workers in that industry can work at home. Figure 6 shows a scatter plot using the industry data between the Dingel-Neiman "stay at home" measure and the decline in paid employment in that 3-digit industry through April 11th using our ADP employee sample. As seen from the figure, there are a few 3-digit industries that saw employment increases since early March including non-store retailers, which include online retailers (NAICS 454) and delivery services (NAICS 492).

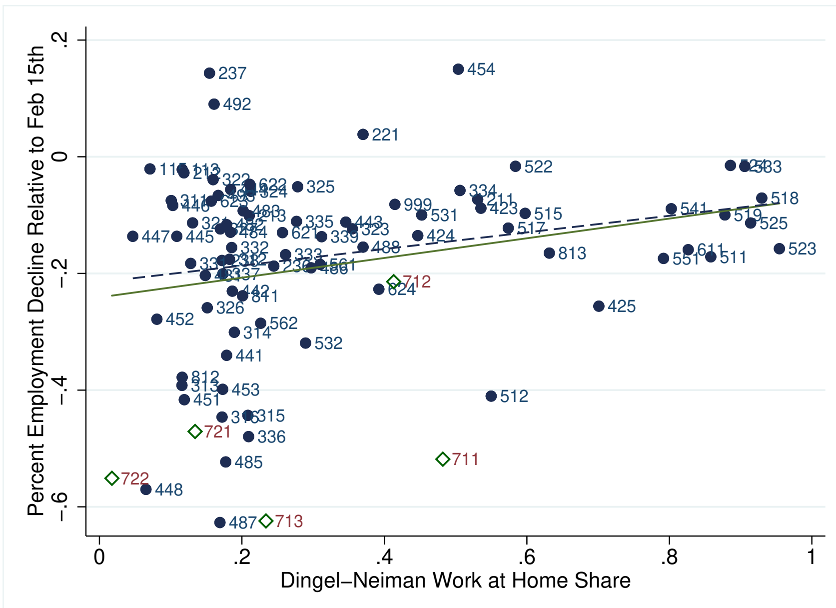
Figure 6 highlights a slight positive relationship between industry-level employment declines and the ability to work at home. The solid line in the figure is a fitted regression line with a slope coefficient of 0.17, a standard error of 0.07, and an adjusted R-squared of 0.05. The dashed line is a fitted regression line excluding the leisure and hospitality industries. The figure shows that the industries that saw the largest employment declines were, on average, industries where workers are not able to do their tasks at home. These industries are in the bottom left quadrant of the figure. However, there are also many industries where workers were not able to do their tasks at home that saw only modest employment declines (the upper left quadrant of the figure). Additionally, outside of the industries with the lowest work at home measures (work at home share greater than 0.3), there was very little relationship between the ability to work at home and industry employment declines. Even the industries where most workers can work at home had employment declines of 15 percent on average since early March. It should be noted that 3-digit industry variation may be too crude a measure to pick up the importance of the ability to work at home in explaining employment declines. The ability to work at home is an occupation-level variable as opposed to an industry-level variable. However, the patterns in Figure 6 suggest that the ability to work at home is not the primary factor explaining cross-industry variation in employment declines.

Column 2 of Table 3 shows the reduction of hours worked for a given worker who has remained employed in that sector through April 11th. The results are only shown for hourly workers. Specifically, we follow a given employed worker from mid-February through mid-April and measure what happened to that worker's hours throughout the recession. Essentially all industries see a decline in hours worked during this period. However, the declines are by far the largest in the social sectors. Continuing hourly workers in the Accommodation/Food Services industries and the Arts/Entertainment industries saw declines in hours worked of roughly 20 percent.

As highlighted above, the decline in aggregate hours was about the same magnitude

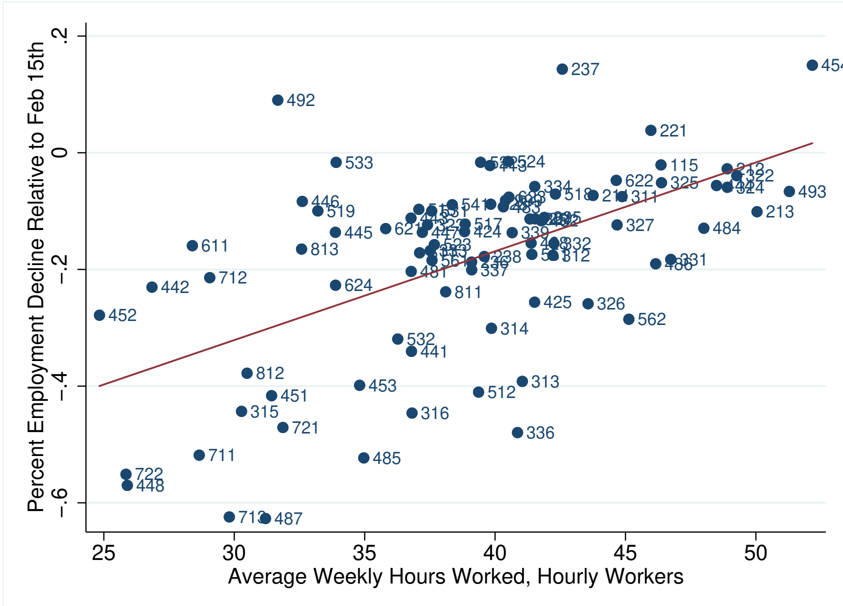
[26] Dingel and Neiman (2020) provide multiple measures for their work at home index. We use their "teleworkable_emp" measure. The patterns in Figure 6 are similar regardless of their measure used.

Figure 6: Relationship Between Dingel-Neiman Work at Home Measure and Actual Paid Employment Declines, 3 Digit NAICS Industry Variation



Notes: Figure shows the variation in the Dingel-Neiman "Work at Home" index and the decline in paid employment at the three-digit NAICS level through April 11th using our employee sample. The leisure and hospitality industries are designated with diamond while all other industries are denoted with circles. The solid line is a fitted regression line across all industries. The dashed line is a fitted regression line through the industries excluding the leisure and hospitality industries. The slopes of the two regession lines are 0.17 (standard error = 0.07) and 0.14 (standard error = 0.06), respectively. Industry points are labeled with their NAICS industry code.

Figure 7: Relationship between Initial Hours Worked and Employment Declines, 3-Digit Industry Variation



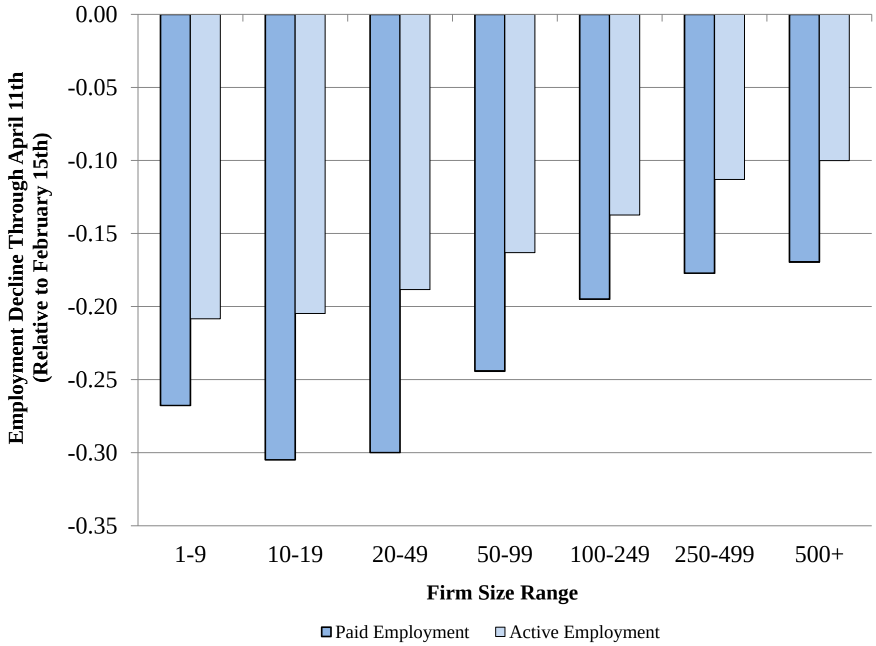
Notes: Figure plots the relationship between weekly hours worked for hourly workers in that 3-digit industry mid-February (x-axis) against employment declines of all workers in that industry through April 11th (y-axis) using our employee-sample. The solid line is the fitted regression line through the industries. The slopes of the regression line is 0.015 with a standard error of 0.002. The adjusted R-squared of the simple regression is 0.31. Industry points are labeled with their NAICS industry code.

as the decline in aggregate employment. Given that the hours of continuing workers are also falling, rough equivalence of the decline in aggregate employment and aggregate hours implies that employment declines are higher in low hour industries. Using cross-industry variation, Figure 7 confirms this implication. The figure plots the average weekly hours worked by hourly workers in mid-February (on the x-axis) against the measured employment declines for all workers in that industry through mid April (on the y-axis). Again, we use our employee sample aggregated to 3-digit NAICS industries. Employment declines were concentrated disproportionately in industries where workers worked lower hours.

4.2 Business Size

Much attention has been given to the preservation of small businesses in the current recession. The \$2 trillion stimulus package signed into law on March 27 makes special provisions to support small businesses through a large expansion in federal small business loans, and a second tranch of small business loan appropriations was signed on April 24. Such focus is not unfounded. Large though it may be, COVID-19 is likely to be a temporary shock to the

Figure 8: Employment Change By Business Size



Notes: Figure shows change in paid employment (darker bars) and active employment (lighter bars) by initial (Feb. 15th) business size, using ADP's business level data. Change in employment is measured between February 15th and April 18th. "Businesses" in the ADP data are the entity that contracts with ADP, and can be either firms, establishments, or parts of businesses according to the Census definitions.

economy. Therefore, a primary determinant of the speed of recovery from this crisis may be the extent to which irreversible dis-investments occur. Financially-constrained firms, such as small and young businesses, may be forced to close if they are unable to pay their employees in the short run. If this happens, the recovery from this crisis may be far more protracted. Indeed, a JP Morgan study from 2016 found that roughly half of small businesses did not have a large enough cash buffer to support 27 days without revenue.[27]

Figure 8 plots the change in employment by initial business size between February 15th and April 18th. For this analysis, we use our business-level sample. Classifying by initial business size avoids the problem of businesses changing size bins between periods, an issue which can be serious in this time period. On the other hand, using initial size necessarily excludes entering businesses, so the growth rates only reflect continuing and exiting busi-

[27] Accessed from https://www.jpmorganchase.com/corporate/institute/document/jpmc-institute-small-business-report.pdf on April 11, 2020.

nesses. This seems like a less serious concern in this context. Indeed, Haltiwanger (2020) shows that applications for new businesses have plummeted during the COVID-19 crisis.

Figure 8 shows that businesses with fewer than 50 employees have been reducing employment at a faster rate than their larger counterparts.[28] However, businesses of all sizes saw massive employment declines during the first months of the current recession. Businesses with fewer than 50 employees saw employment declines of more than 25 percent, while those with more than 100 employees saw declines of 15-20 percent. These results are not overly surprising in light of the industry results documented above. The industries that were hit hardest in the beginning of the pandemic recession also tend to be the industries with the smallest businesses as documented by Hurst and Pugsley (2011). Therefore, some of the differential decline in employment of small businesses is likely due to the fact that small businesses disproportionately populate industries like restaurants and entertainment activities.

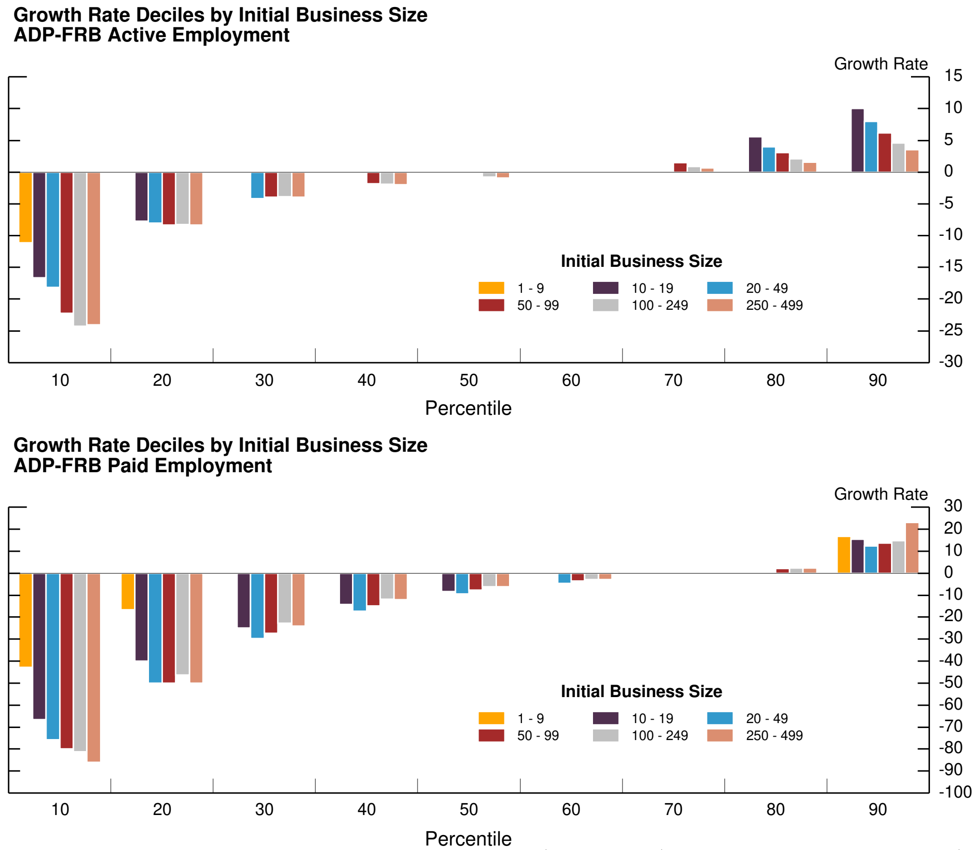
Figure 8 hides interesting heterogeneity across businesses. In Figure 9 we report the entire distribution of employment changes among small businesses of various sizes, limiting our focus to businesses that survive through this time period (continuers) so we can study a meaningful growth distribution. Specifically, for this figure, we only focus on businesses with fewer than 500 active employees as of mid-February. For each initial employment size class, we report percentiles of employment change between February 15 and April 18th. The top panel corresponds to changes in active employment, while the bottom panel corresponds to changes in paid employment.

We focus first on active employment, which shows markedly smaller declines than paid employment (note the differing y-axes between the two panels). Among the smallest initial size class (1-9 employees), the 10th percentile firm saw employment declines of 10% over this period, though employment change was zero across the rest of the distribution (deciles); this may be due to "integer problems" (i.e., for very small business units, even a single employee layoff represents a substantial change in business scale), or it may reflect selection issues in which businesses of this size that come under stress must exit entirely rather than shedding employment (in which case they do not appear in these calculations); indeed, further below we will discuss evidence of substantial exit among small businesses.

Within the next size class (10-19 employees), however, the 10th percentile business saw an active employment decline of more than 10 percent over this period, and the 90th percentile business saw gains of almost 10 percent. It is striking that many businesses saw substantial employment gains over this period, even though the figure is limited to busi-

[28] Here we again emphasize that ADP payroll units may not map directly to either business or establishment concepts used in official data.

Figure 9: The Distribution of Employment Change by Business Size Among Small Businesses



Notes: Figure shows change in active employment (top panel) and paid employment (bottom) by initial business size and employment change decile using ADP's business level data. We limit attention to businesses with less than 500 employees. Exiting businesses are excluded. Change in employment is measured between February 15th and April 18th. "Businesses" in the ADP data are the entity that contracts with ADP which is a combination of the Census notion of firms and establishments.

nesses traditionally thought of as "small" (i.e., fewer than 500 employees). The median business in every size class saw close to zero change in active employment, with positive gains among many above-median businesses. We observe significant dispersion in outcomes, the interdecile ranges above 25 percentage points for all but the smallest size class.

We next turn to the bottom panel of Figure 9, which illustrates the employment change distribution in terms of *paid* employment. Here we see substantially larger moves. The 10th percentile business within every size class saw declines of at least 40 percent, with the largest class shown (250-499) seeing a decline of more than 85 percent. Even the smallest business size class (1-9) saw substantial declines. This panel also reveals extremely wide dispersion in outcomes; the interdecile range of paid employment change varies from 60 percentage points among the smallest businesses to almost 110 percentage points for the 250-499 size class. Of course, "integer problems" may be playing a role among the smallest businesses.

Interestingly, Bartik et al. (2020a) (using rich Homebase data on small business hourly employment and hours) find that declines in hours worked between January and mid-April are driven almost entirely by business shutdowns (i.e., zero hours worked in a week) and hours reductions among retained employees, with minimal contribution from layoffs of hourly employees.[29] Figure 9 is not markedly inconsistent with this while adding considerable color. The median small business shows little movement in either active or paid employment between mid-February and early April, suggesting minimal layoffs among that group. But underlying this median result is considerable distributional variation: a bit less than half of surviving businesses experienced nontrivial employment declines, and a few businesses experienced dramatic declines exceeding 80 percent. On the other hand, some businesses have experienced sizable employment gains. That being said, some modest tension remains between the results of Bartik et al. (2020a) and our results from ADP data in this section and elsewhere in this paper. Generally speaking, in other sections we have documented substantial declines in both paid and active employment among continuing businesses, and Figure 9 shows that the half of businesses showing declines in active employment saw declines that are larger in magnitude than the gains among the roughly half of businesses that saw employment increases; and for paid employment, declines are seen up to the 60th percentile of small businesses. In other words, ADP data do suggest substantial layoffs among continuing businesses. A possible reason for this discrepancy is that Bartik et al. (2020a) observe business shutdowns when zero hourly employees clock in; it is possible that some businesses are staying "open" with at least a few salaried employees, so they count as continuing businesses in ADP data despite registering no hourly employment. Additionally, our results

[29]Homebase data track "local" types of businesses with concentration in retail and leisure and hospitality industries.

are representative of the entire U.S. economy. Some of the differences between our results and those in Bartik et al. (2020a) stem from differences between the leisure and hospitality sector which dominate the Homebase sample and the aggregate of all sectors in the ADP sample as highlighted in Tables 2 and 3.

Taken together, the various insights from Figure 9 reveal striking heterogeneity in the experiences of small businesses. The relatively muted moves in active employment (relative to paid employment) might, one would hope, suggest that many businesses do not see their layoffs as permanent at least through the first month of the recession, while the extreme declines in paid employment among more than half of small businesses leave ample room for concern about the state of the small business economy.

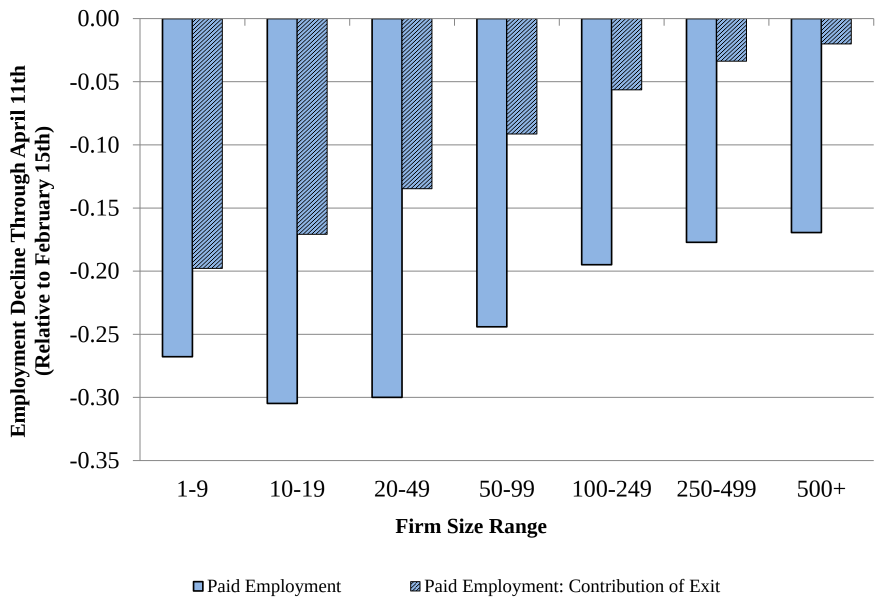
4.3 Exit and Business Size

The data shown on Figure 9 necessarily abstract from business exit, allowing for a focus on the distribution of employment growth experiences across businesses of different sizes. Like other private-sector microdata, ADP data are not usually well-suited to studying business exit since exit from the ADP sample may reflect changes in payroll processing preferences in addition to true business exit. In the COVID-19 era, however, threats to business survival are significantly elevated such that exit from the ADP sample is likely to be informative about true exit. We next focus on the contribution of exit to overall growth patterns.

Figure 10 shows paid employment growth by business size class among both continuers and exiters, as in Figure 8 above. We repeat the total employment change from Figure 8 (which includes continuers and exiters together), shown on the solid bars of Figure 10. The cross-hatch bars show the contribution from exit alone; mechanically, this is the employment share of exiters (in the initial period) times the growth rate of the exiters (-1). Intuitively, the contribution of exiters tells us what growth would have been if continuing businesses had been held to zero growth. It is evident that the exit margin has played a very large role in overall employment declines for small businesses, and less of a role for larger units. Indeed, more than half of the employment losses at businesses under 20 workers were due to exit. This is qualitatively consistent with the findings of Bartik et al. (2020a) discussed above as well as Kurmann et al. (2020); moreover, it is not surprising in light of Figure 9, which shows only modest paid employment decline among the median continuing small businesses. For business employing more than 500 workers, in contrast, exit accounted for less than one sixth of job losses.

The main takeaway from Figure 10 is that, on average, the stark employment declines at small businesses are mostly due to businesses shutting down, whether temporarily or perma-

Figure 10: Employment Change by Business Size, Contribution of Exit



Notes: Figure shows change in paid employment by initial business size using ADP's business level data. Crosshatched bars show the contribution of exit: the Feb. 15th employment share of exiters times their growth rate (-1). Change in employment is measured between February 15th and April 18th. "Businesses" in the ADP data are the entity that contracts with ADP, and can be either firms, establishments, or parts of businesses according to the Census definitions.

nently, even while Figure 9 shows a range of experiences, including significant employment declines, even among survivors. In any case, shutdowns that become permanent may slow the eventual recovery, as relationships between workers, customers, suppliers, and businesses are dissolved.

4.4 Worker Demographics

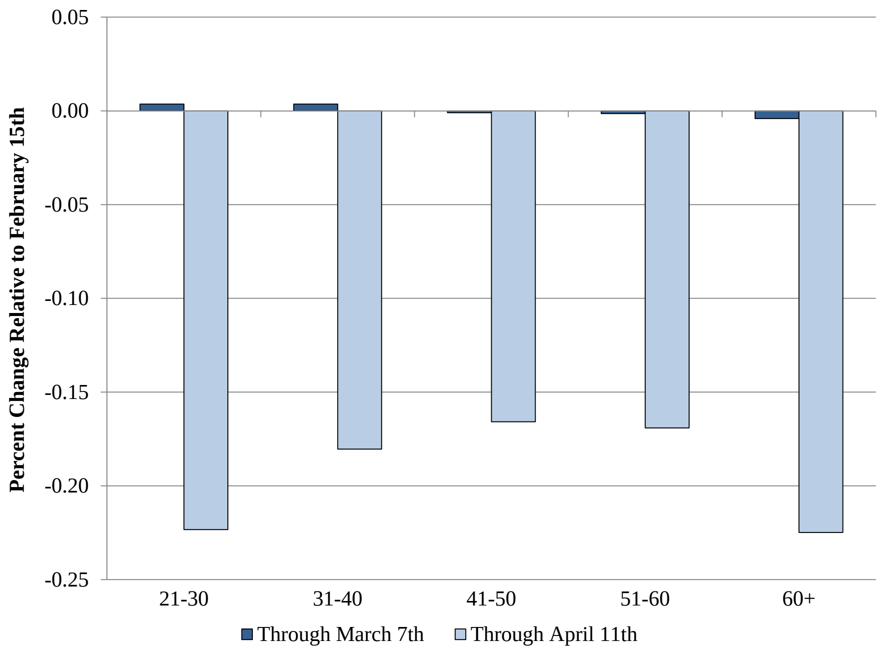
We next explore differential effects by worker gender and age. Figure 11 plots employment changes between mid-February 2020 through early-April 2020 by 10-year age bins. The darker bars plots the change between Feb 15th and March 7th as a baseline. The lighter bars plots the change between March 7th and April 11th during the recession. The figure shows an inverted-U between age and employment declines. The youngest workers—those between the ages of 21 and 30—saw employment declines of 22 percent. Young workers historically experience larger declines in recessions relative to older workers.[30] Also, younger workers are concentrated in industries hit hardest by the recession such as leisure and hospitality activities. In contrast, workers between the ages of 31 and 59 saw employment declines of about 17 percent. However, older workers—those over 60—also saw larger employment declines of 22 percent. These older workers have a slightly higher baseline exit rate from the employed pool prior to the recession starting due to natural retirement. However, this baseline exit rate is orders of magnitude smaller than the employment declines during the beginning of the recession: in the 3 weeks *prior* to March 7, employment in this group only declined 0.5 percent. We also explore patterns separately by gender. The declines in employment were slightly larger for women relative to men: 21.5 percent vs. 17.8 percent, respectively. This difference likely reflects differences between the sorting of men and women into industries that were differentially hit by the recession.

4.5 By Region

The spread of COVID-19 has not been uniform across the country. The virus is transferred through interpersonal interaction; as a result, urban areas have generally seen more aggressive spreads of the virus. There were over 300,000 conestablishmentsed cases and over 22,000 deaths in New York as of April 28th, compared with 46,000 cases and 1,800 deaths in California. Meanwhile, states have also differed broadly in their policy directives to combat the virus. California encouraged social distancing measures as early as March 11 while travelers continued to congregate on Florida's beaches. Indeed, research shows that the

[30]See, for example, Hoynes et al. (2012).

Figure 11: Employment Changes by Age



Notes: Figure shows employment declines by different age ranges through March 7th (darker bars) and through April 11th, 2020 (lighter bars). All changes relative to February 15th, 2020. Employee sample is used for this analysis. Data are weighted so that the sample matches aggregate employment shares by 2-digit industry cross business size.

Table 4: Employment Changes for Sixteen Largest States Through Early April

State	Employment Change	State	Employment Change
Michigan	-28.6%	Ohio	-17.7%
New York	-25.5%	Georgia	-17.3%
Massachusetts	-23.5%	Texas	-17.3%
New Jersey	-22.8%	Illinois	-17.1%
Pennsylvania	-21.5%	North Carolina	-17.0%
Washington	-18.5%	Virginia	-16.4%
California	-18.3%	Tennessee	-16.1%
Florida	-17.7%	Arizona	-11.6%

Notes: Table shows decline in employment for the sixteen largest U.S. states based on population through April 11th, 2020. All changes are relative to February 15th, 2020. We use our employee-level sample for this analysis. All data are weighted such that the sample matches aggregate employment by business size cross 2-digit NAICS industry.

change in travel behavior of individuals, scraped from cell phone location data, has been heterogeneous across the country.[31]

These differences have manifested themselves somewhat in the labor market as well. Table 4 reports the change in employment in the 16 most populous states through April 11th. Michigan had the largest decline, with 28.6% of workers losing their paychecks. New York, Massachusetts, New Jersey, and Pennsylvania also each saw employment declines of over 20 percent in the ADP data. In comparison, Arizona had a smaller decline in employment of 11.6%. All of these other large states had employment declines between 16 and 19 percent. The results in Table 4 should be interpreted with some caution. These are weighted to match national employment shares by industry and firm size and not adjusted for potentially non-representative business size and industries within the state. However, they do suggest that some of the states that were hit hardest with the pandemic (Michigan and the Northeast) had larger initial employment declines.

5 Distributional Effects across Workers

In this section, we explore the labor market outcomes for workers at different points of the wage distribution at the beginning of the current downturn. We then explore how much of these differential declines can be explained by the fact that workers at different points in the

[31] See https://www.nytimes.com/interactive/2020/03/23/opinion/coronavirus-economy-recession.html, accessed April 11, 2020.

wage distribution are employed in different types of businesses which have had differential exposure to the COVID-19 shock.

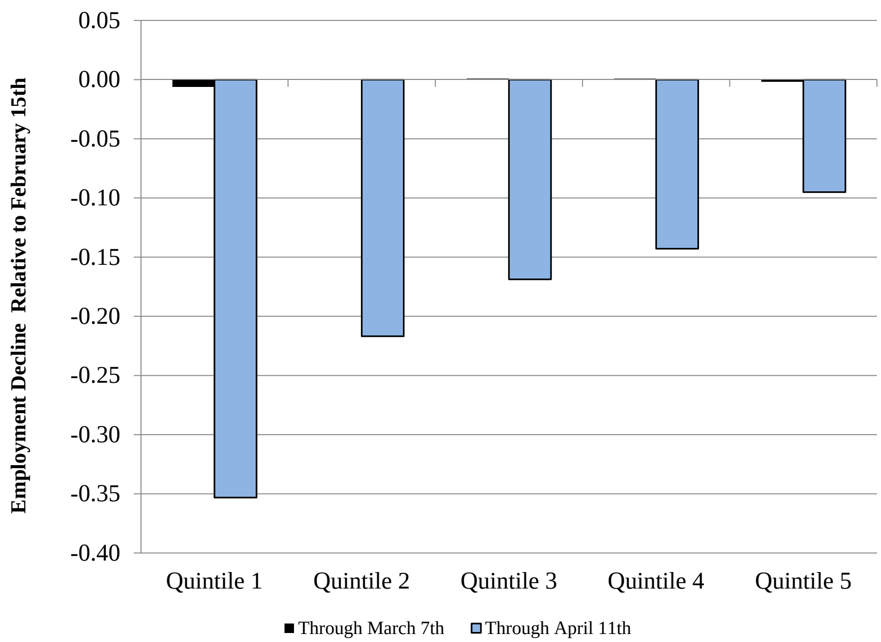
We first segment workers by their initial place in the wage distribution. Specifically, we use early March data to define wage quintiles for our analysis based on a worker's administrative base hourly wage. We pool together hourly and salaried workers when making our quintiles. For hourly workers, we use their exact hourly wage. For salaried workers, we assume the workers are working 40 hours per week when computing their hourly wage. For weekly (biweekly) salaried individuals, this is just their weekly (biweekly) base administrative earnings divided by 40 (80). We hold these thresholds fixed throughout all other weeks of our analysis. The nominal thresholds for the quintiles are 13.5, 16.41, 24.53 and 32.45 dollars per hour.[32]

Figure 12 shows the employment declines through April 11th for workers at different quintiles of the initial wage distribution. The dark bars measure changes from February 15th through March 7th while the lighter bars measure changes from February 15th through April 11th. As seen from the figure, employment declines in the initial stages of this recession are disproportionately concentrated among lower wage workers (quintile 1). While employment rates fell for workers throughout the wage distribution, workers in the top quintile (quintile 5) had employment declines that were roughly one-fourth as large as the employment declines for workers in the bottom wage quintile. Employment declined by 35 percent for workers in the bottom quintile of the wage distribution during the first four weeks of this recession. Employment declines are monotonic in the percentile of the wage distribution. Workers in the second quintile reduced their employment by roughly 22 percent while the median worker (those in the third quintile) reduced their employment by about 17 percent. The workers in the top two quintiles experienced employment declines of 14 and 9 percent, respectively.

The numbers above imply that 36 percent of the aggregate employment declines during the beginning of the recession occurred in the bottom quintile of wage-earners, compared with 22%, 17%, 15% and 10% for the 2nd, 3rd, 4th, and 5th quintiles, respectively. Given the total estimated loss of 27 million jobs in the private sector over the past month, this implies that nearly 10 million bottom-quintile workers have left employment. During the Great Recession, *aggregate* private non-farm payroll declined by 8.5 million in total: the present loss of low-wage worker employment is on the order of magnitude of the entire economy's employment loss during the Great Recession. Recessions always tend to reduce employment rates more for lower skilled workers, and this downturn so far is no different. However, the

[32]These cutoffs match well the distribution of wages in the 2019 March Supplement of the Current Population Survey (CPS). Computing hourly wages as annual earnings last year divided by annual hours worked last year, the 20th, 40th, 60th, and 80th percentile of hourly wages (measured in nominal dollars per hour) in the 2019 CPS were 12.0, 17.1, 24.0, and 36.1 (author's calculation).

Figure 12: Employment Changes By Initial Wage Quintile



Notes: Figure shows decline in employment for workers in different initial wage quintiles through March 14th, 2020 (dark bars) and through April 11th, 2020 (lighter bars). Employment declines measured relative to February 15th. Data for this figure use the employee sample. All data are weighted such that the sample matches aggregate employment by 2-digit NAICS cross business size.

magnitude of the difference between high and low-wage workers is historic. This recession is amplifying income inequality given that the employment losses are so disproportionately concentrated at the lower end of the income distribution.

How much of the larger decline in employment among low-wage workers can be attributed to the industrial composition of the COVID-19 shock? Low-wage workers are more likely to work in restaurants, retail, and leisure services and are also more likely to work in smaller businesses. Low-wage workers tend to be younger which, as shown above, had larger employment declines. Finally, some of the differences in Figure 12 may be due to the fact that low-wage workers have higher separation rates in general. To assess whether differential exposure to the recession by business characteristics (industry and business size) or worker characteristics (age, gender, and location) can explain the differential pattern across the wage distribution, we further exploit the panel nature of our data and estimate the following linear probability model with OLS:

$$S_{ijt} = \sum_{q=1}^{5} \mathbf{1}\{i\text{'s quintile is } q\} \cdot (\alpha_q + \beta_q * Post_t) + \delta Post_t + \Gamma X_{ijt} + \theta X_{ijt} * Post_t + \epsilon_{ijt} \quad (1)$$

where S_{ijt} is an indicator equal to one if worker i separates from firm j between month t and $t+1$ and $\mathbf{1}\{i\text{'s quintile is } q\}$ is an indicator equal to 1 if i's base wage quintile is q. $Post_t$ is an indicator equal to 1 if considering separation probabilities between mid-March and mid-April. We include observable business- and worker-level controls X_{ijt} in some regressions.

For this regression, we include two cohorts of worker-business pairs. First, we include workers who are paid by their business in either of the first two weeks of February and see whether the worker is paid by their business in either of the first two weeks of March. Second, we include workers who received a paycheck in either the first two weeks of March and see whether the worker is paid by their business in the first two weeks of April. For this analysis, we again only include workers who are paid weekly or biweekly. Finally, we only include businesses that remain in the sample over the entire period from early February through early April. As with the analysis in Figure 12, we define the quintiles in early March based on the aggregate wage distribution within the ADP sample and hold the quintile boundaries fixed when sorting workers into the quintiles during early February.

We control for worker i's wage quintile at the beginning of the period to allow the baseline separation rate to differ for workers in different quintiles q. The baseline separation probability of workers in quintile q is captured by α_q. Our variable of interest is how the separation probabilities of each quintile change during the beginning of the recession. This is captured by the coefficients β_q on the interaction of the wage quintile dummies with the dummy variable $Post_t$. We then ask how these β_q coefficients change as we include various

Table 5: Monthly Separation Regressions for Wage Quintiles

	(1)	(2)	(3)	(4)	(5)
Post × Wage Quintile: 1	0.145	0.125	0.123	0.112	0.122
	(0.017)	(0.018)	(0.010)	(0.025)	(0.012)
Post × Wage Quintile: 2	0.071	0.068	0.067	0.062	0.065
	(0.013)	(0.011)	(0.015)	(0.020)	(0.005)
Post × Wage Quintile: 3	0.047	0.045	0.043	0.041	0.045
	(0.008)	(0.007)	(0.006)	(0.018)	(0.007)
Post × Wage Quintile: 4	0.020	0.018	0.017	0.016	0.019
	(0.004)	(0.004)	(0.007)	(0.016)	(0.004)
Observations (millions)	27.0	27.0	27.0	26.9	26.9
Mean of Dep. Var.	0.087	0.087	0.087	0.087	0.087
Industry Fixed Effects	N	Y	Y	Y	Y
Business Size Fixed Effects	N	N	Y	Y	Y
Demographic Controls	N	N	N	Y	Y
State Controls	N	N	N	N	Y

Notes: Table shows estimates of regression (1). The various columns include different business and worker fixed effects. *Post* x *Wage Quintile*: q shows the coefficient β_q from the regression. This is the differential separation rate for workers in quintile q during the recession period (mid-March to mid-April) relative to the separation rate of workers in the top wage quintile. Robust standard errors clustered at the 3-digit industry-business size level.

business and worker controls, X_{ijt}.

Table 5 shows the β_q coefficients across various specifications of equation (1). The first column shows our estimates including no additional X_{ijt} controls. We omit the coefficient from quintile 5 (the top wage quintile). As a result, all coefficients should be interpreted as the relative employment declines in quintiles relative to quintile 5. The baseline separation probability between February and March is approximately 5.6 percentage points higher for bottom quintile earners than that of top quintile earners. After controlling for wage quintile fixed effects, bottom quintile earners were 14.5 percentage points more likely to separate from their employer between March and April than were top quintile earners, reflecting the patterns in Figure 12.[33] The increase in separation probabilities declines monotonically throughout the base wage distribution.

Recent research by Mongey et al. (2020) suggests that low-income workers tend to work in "social" sectors and the large decline observed in these sectors will result in job loss concentrated among lower wage workers. Column 2 explores this hypothesis by introducing

[33]The results in Table 5 are not directly comparable to those in Figure 12 given that we are focusing on a balanced panel of businesses. Some of the additional employment decline we highlight in Figure 12 is due to business exit.

2-digit NAICS industry fixed effects as additional regressors. Including industry fixed effects reduces the gap in excess separation rates between bottom quintile earners and top quintile earners only slightly to 12.5 percent. Therefore, a differential industry mix can explain 13.8% (2/14.5) of the gap in job loss between low-wage and high-wage workers during the beginning of this recession, but a substantial gap remains even after accounting for industrial composition. Column 3 includes additional fixed effects for initial business size. Doing so has little effect on the distribution of employment shifts.

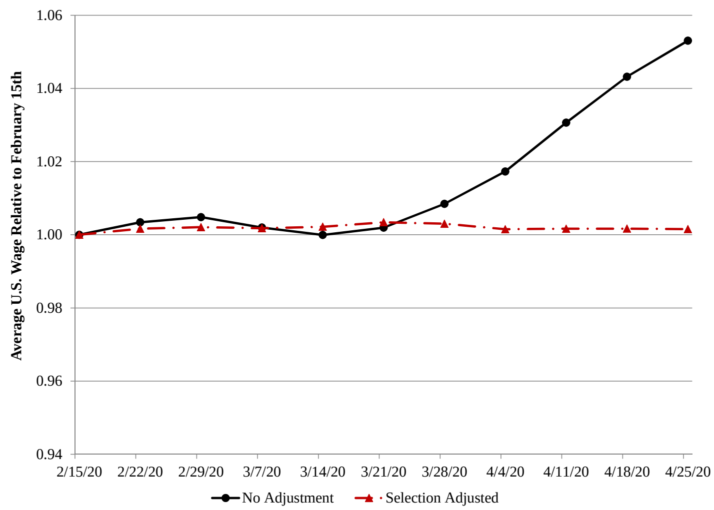
Column 4 also includes fixed effects for worker demographics; namely, 5-year age bins and gender. This reduces the gap in excess separation probabilities between low-wage and high-wage workers to 11.2 percent. This decline is driven by the age effects. As seen above, younger workers were more likely to be displaced, and younger workers systematically have lower wages. This additional 1.3 percentage point reduction in excess separations suggests that the differential age and industry composition of low-wage workers can jointly explain approximately one-fifth of the gap between low- and high-wage worker employment behavior during the early stages of the Pandemic Recession. Finally, column 5 includes state fixed effects. Doing so reinflates the gap between top and bottom quintile workers to 12.2 percent, suggesting that low-wage workers are disproportionately in states which do not have large employment declines. Indeed, Michigan, New York, New Jersey, and Massachusetts tend to have higher wages, on average, than other large states with smaller employment declines such as Arizona and North Carolina.

Overall, we conclude that there is a substantial difference in the behavior of low- and high-wage workers during the early stages of the Pandemic Recession. This difference can only partially be accounted for by differences in industry, business size, demographics, or location: after controlling for all of these observable characteristics, separation rates still rose by 12.2 percentage points more for bottom quintile earners than they did for top quintile earners. Therefore, the Pandemic Recession has had significant distributional consequences. We now turn to consider the behavior of wages at the beginning of this downturn.

6 Wage Changes during the Beginning of the Pandemic Recession

Figure 13 shows the trends in wages in the economy during the pandemic recession. The solid line creates a wage index by measuring the mean base wage of all working individuals in the economy. Since the start of the recession, observed base wages in the ADP sample grew by nearly 6 percent. As highlighted in Solon et al. (1994), the changing composition of workers

Figure 13: Trend in Base Wages, Controlling for Selection

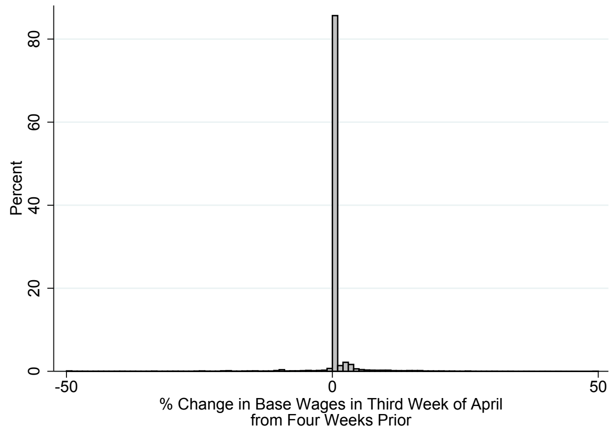


Notes: Figure shows trends in weekly wages between the periods of February 15th and April 25th, 2020. The solid line (circles) averages base wages across all employed workers in each period. The dashed line (triangles) controls for selection by measuring the base wage of a given worker over time. All data are weighted so that the ADP primary sample matches aggregate employment shares by 2-digit industry cross business size.

over the business cycle can distort measures of the cyclically of wages. Recently, Grigsby (2019) documents that measured growth in average wages has become countercyclical during the last few recessions. He documents that the changing selection of workers during the recent recessions has been responsible for the observed countercyclicality of wages. As seen from Figure 12, workers at the bottom of the wage distribution were much more likely to have employment reductions than those at the top of the wage distribution. This means that throughout this period, the sample is becoming more selected towards higher-earning individuals.

To assess the importance of selection, we again exploit the panel nature of the ADP data. In particular, we compute base wage growth for a sample of continuing workers. By considering individual wage *growth* rather than *levels*, we restrict attention to workers who are in the sample in consecutive periods, thereby purging the wage series of the principal form of selection. We then produce a selection-adjusted wage index by chain-weighting this average wage growth from the reference week ending February 14. The result of aggregate wage growth adjusting for selection is shown in the dashed line in Figure 13. Two things are of note. First, there is essentially no nominal wage growth for continuing workers during

Figure 14: Distribution of Base Wage Changes for Continuing Workers Through April 18th



Notes: Figure shows distribution of base wage change for continuously employed workers between March 20th and April 18th, 2020. The data we show here are the unweighted distribution of wage changes.

this period. Given that most people do not receive wage changes during a given 4 week period, this is not surprising. Second, and more importantly, there is no break in trend at the start of the recession. In other words, worker wages have not yet responded to changes in economic conditions. All of the labor adjustment by businesses has occurred, so far, on the quantity margin and not on the price margin. The dashed line in Figure 13 combined with the results of Figure 12 imply that aggregate average wages grew in the first few weeks of the recession solely because of selection effects. Low-wage workers have disproportionately left the labor market while continuing workers had no change in wage trajectories.

As the recession continues, wages will likely adjust. Grigsby et al. (2019) document that during the Great Recession, businesses were increasingly likely to cut the nominal base wages of their workers as the recession progressed. Additionally, wage growth for continuing workers slowed considerably during the Great Recession. As of now, businesses have not cut the base wages of their existing workers. Figure 14 shows the base wage change distribution for continuing workers between March 13th and April 18th. Consistent with the results in Grigsby et al. (2019), essentially no worker receives a nominal wage cut during normal times. During the first month of the current recession, workers have yet to receive nominal base wage decline on the job, though this may change in the coming months.

7 Conclusion

In this paper, we use high-frequency payroll data from ADP to track the behavior of the labor market in the wake of the recession that was likely started by the global COVID-19 pandemic.

The data have several advantages over commonly employed labor market indicators. First, the data are large and of high quality, coming from administrative reports of paychecks for around 26 million individuals. Second, the data come at a weekly frequency with essentially no lag. Third, they provide information on employment, hours, earnings, and wages, as well as characteristics of both workers and businesses. Fourth, they track individual workers and businesses through time, allowing for a complete study of the characteristics of workers and businesses contracting their labor input.

The data show an unprecedented collapse in employment from mid-February through mid-April. Aggregate employment fell 22 percent during these weeks. This constitutes a decline which is approximately three times the raw peak-to-trough change in employment seen during the Great Recession. The fact that this decline has occurred over the course of just a few weeks is similarly staggering—in every prior US recession for which we have monthly data, the peak-to-trough employment decline took at least 11 months to manifest.

While the majority of the employment decline occurred among continuing businesses, measured business exit—or temporary suspension of operations—plays a substantial role in the overall collapse, particularly among smaller businesses. This is an alarming pattern which may have relevance for the pace of recovery. One would hope that many of the businesses we observe suspending activities will resume operations in the near future. If not, the jobs destroyed by exiting businesses are permanently gone, requiring extra growth among surviving businesses or extra business entry to replace them. Jobs and the associated personal toll of unemployment are not the only costs of business failure. From the perspective of business owners, the failure of a business means the loss of income and probably a large share of household assets. From the perspective of the macroeconomy, business failures mean the destruction of intangible capital and even the loss of some physical capital, particularly in light of costly capital reallocation. From the perspective of communities and neighborhoods, business failure means dramatic, sometimes irreversible changes to the local physical economic landscape. While some recessions see elevated failure of low-productivity businesses (thereby enhancing aggregate productivity), we have no reason to expect exit selection to function constructively in the current environment, where business revenue losses are determined by the rapid onset of a health crisis.[34]

These employment declines are not evenly spread throughout the wage distribution. The overwhelming brunt of the employment decline is concentrated among lower-wage workers. The bottom 20 percent of wage-earners account for nearly 36 percent of all job loss. These differences persist even after controlling for differential declines by industry, business size, worker age, and location. The large exit of low-wage workers from the labor market has

[34]See Foster et al. (2016) on productivity selection and exit in recent recessions.

resulted in average wage per worker *rising* by five percent in the weeks following the start of the recession. However, all of this is driven by selection effects. Following a given worker through the start of the recession, we find that the wages of continuing workers have been flat. At this point of the recession, essentially all of the adjustment has occurred on the quantity margin. Most of the quantity adjustment has been on the extensive margin of labor supply. However, the intensive margin of labor supply has also declined slightly.

Although the "recession" is only weeks old, the size of the labor market decline has been unprecedented, and the incidence of the decline across the worker and business distributions has been alarming. How long the downturn lasts likely depends on the speed at which a vaccine is developed, testing and tracing is expanded, or treatments are found that could mitigate the mortality rate of the disease. In the meantime, the collapse in activity is having a disproportionate effect on small businesses and lower-wage workers: precisely those without the cash flow and savings to smooth consumption. The longer the current situation persists, the greater the likelihood that lower-wage workers may suffer the disproportionate brunt of the "recession" and that the recovery will depend on a markedly reduced number of operating businesses. Future work should closely monitor labor market outcomes as well as consumption and other socio-economic variables of lower wage workers throughout the current economic situation and as the eventual recovery takes hold.

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